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Bandwidth Optimization Algorithms In Federated Learning: A Comprehensive Review

Communication-Efficient Strategies For Decentralized Machine Learning

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Abstracta

Federated learning allows several devices to train decentralized models while preserving local data, however because of the frequent and significant model changes, it poses significant bandwidth challenges. In real-world applications, scaling these systems necessitates efficient bandwidth management. Numerous tactics are examined in this study, such as compression methods, network innovations, and adaptive protocols. To reduce update sizes without compromising accuracy, we look at methods including model pruning, quantization, and sparse updates. Faster data transfers are made possible by network developments like hierarchical federated learning and asynchronous communication, while adaptive protocols adjust communication based on client accessibility and network conditions. By looking at current advancements and trends, we provide a summary of the literature, identify gaps, and suggest creative ways to increase the efficacy and scalability of FL systems. The objective of this work is to direct further investigations into improving bandwidth management strategies for federated learning.

Keywords: Federated Learning, Bandwidth Optimisation

1. INTRODUCTION

Since its initial proposal in 1956, artificial intelligence (AI) as well as its technology advancements are having an effect on people lives that is growing in importance [1]. Recent developments in artificial intelligence technology have opened up a wide range of application areas [2]. For machines to truly mimic human reasoning, vast amounts of real data must be used for training. By allowing centralized modelling training across numerous devices while maintaining data on local devices, federated learning transforms the machine learning space. Google first introduced the FL concept in 2016 with the primary goal of updating the model on Android smartphones without revealing private information [3]. Google then used a FL system that was application-focused. The architecture of the FL system was created to execute the FedAvg algorithm for mobile, undertake federated investigations and track statistics for massive cluster equipment without keeping raw device data on cloud servers. In the realm of data protection computing, the FL is one of the most important technologies. Due to its deployment approach and lightweight technological paths, Federated Learning is a well-liked product and solution for numerous privacy computing applications. A significant number of research accomplishments in the subject have surfaced as FL applications have developed and become increasingly complicated. This method enhances security and privacy while enabling several data sources without the need for centralized data collection.

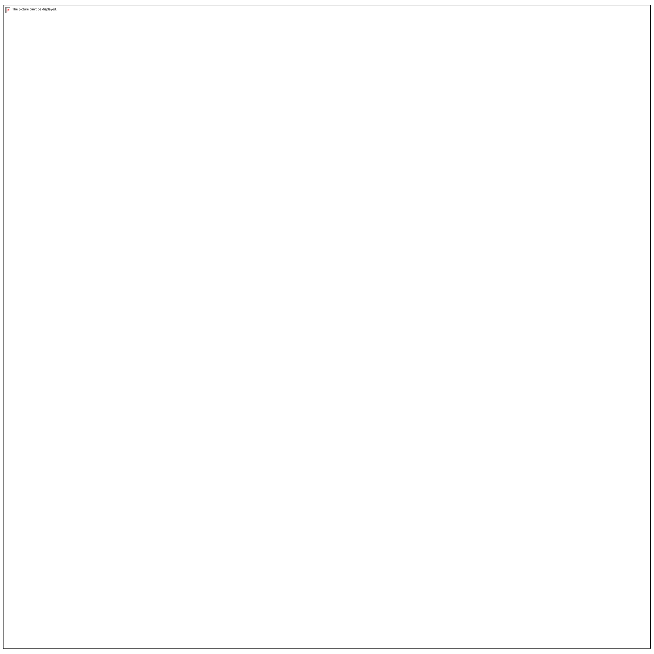

Figure 1*: Local updates of federated learning are transmitted to a central server.*

To the extent that confidential data remains local, FL is a secure distributed machine learning technique that may be applied to a range of distributed edge servers and devices using FL algorithms. [4]. FL provides data training tasks to each local client, and clients and servers interact with each other using parameters rather than directly exchanging data. Then, the server's contribution to global model updating is restricted to simple parameter aggregation. Such a FL system can protect local user data by reducing server processing and storage resources. FL can generate a better global model with client-server communication. The approach differs from traditional centralized training, which collects all local data and stores it on a central training server [5]. In contrast to conventional centralized machine learning techniques [6], FL methods allow several federated authorities to build a single, safe, and compatible model for ecological systems using multiple sources of data [7]. Federated learning has many issues, particularly with bandwidth control, but it also offers a lot of potential. The frequent and often huge model updates transfer between the clients and central server result in significant bandwidth requirements. Effective control of this bandwidth is required in order to grow federated learning systems and make them feasible for usage in practical uses.

Current advancements and emerging trends in these domains are the main focus of our review. We give a thorough review of the state of the subject, identify knowledge gaps, and present innovative suggestions for improving Federated learning systems' efficacy and scalability. Through theoretical analysis and practical examples, we hope to provide direction and ideas for additional study aimed at developing further effective solutions for federated learning bandwidth management.

2. TECHNIQUES FOR EFFECTIVE BANDWIDTH CONTROL IN FEDERATED LEARNING

Numerous issues plague federated learning, particularly with regard to bandwidth control. because model updates are exchanged so frequently and in such big quantities. Numerous strategies have been developed to solve these issues, with an emphasis on controlling data distribution and enhancing communication effectiveness. Here are a few of the fundamental techniques applied to this subject:

2.1. Model Compression Techniques

Compression of the model strategies are required to decrease the quantity of model enhancements sent from the clients to the central main server in order to conserve bandwidth.

According to Han et al. (2016) [16], pruning is the process of eliminating superfluous weights from a neural network without noticeably affecting performance. The model is made sparser and more effective by removing nodes or weights that are not as important. For example, pruning may eliminate 500 of the least significant connections from a neural network's original 1,000 connections, therefore splitting in half the model size.

Another method is the quantization, which reduces precision of the model parameters to require fewer data. According to Gupta et al. (2022) [17], converting 32-bit floating-point values to 8-bit integers for weights and activations can reduce the quantity of the data by a factor of four. This basically means that instead of a 32-bit floating-point value, a weight is provided as an 8-bit integer.

Although not explicitly discussed in the studies that were supplied, sparse updates are a widely accepted idea in the literature. By delivering updates solely for areas of the model that have seen major changes, this strategy greatly reduces communication by only send changes in model weights that surpass a certain threshold. For instance, the communication may be reduced by up to 90% if just 10% of the model weights change notably during training and only these modifications are sent.

2.2. Adaptive Protocols

By adapting constantly to the state of the network and client availability, adaptive protocols are essential for streamlining communication in federated learning systems. According to Kairouz et al. (2021) [18], dynamic client selection means selecting a portion of clients with the best connectivity for every training cycle, preventing pauses and using less bandwidth.

Chen (2023) [19] studied adaptive frequency, which adjusts the model's update frequency according to the model's rate and network circumstances of convergence. This technique helps manage congestion during times of high network traffic by lowering the update frequency to avoid network overload. These studies show how adaptive protocols, such as adaptive frequency and dynamic client selection, enhance the efficacy of federated learning by adapting communication based on the circumstances.

2.3. Network Innovations

For federated learning systems to improve their communication architecture and protocols, network advancements are essential. In order to lessen the communication load on the central server, Yang et al. (2019) [20] explain hierarchical federated learning, which arranges clients into hierarchical structures. The quantity of connections that go straight to the central server is reduced by clustering clients with local aggregators. To reduce the communication load, for instance, a company with several branches could have a local aggregator in each branch that communicates with the central server and aggregates updates.

Instead of synchronize all client simultaneously, asynchronous communication permits clients to send updates independently. With this approach, clients can give updates according to their local timetables. For example, customers in various time zones can send updates once their training rounds are over. Zhao et al. (2022) [21] emphasize the benefits of this strategy for enhancing scalability and controlling communication delays ("Federated Learning with Non-IID Data: A Survey"). These network advances, like Communication that is asynchronous and hierarchical, increase the efficiency and expandability of federated learning systems by simplifying communication protocols and reducing server load.

2.4. Data and Model Optimization

More effective use of bandwidth can also be achieved by streamlining the handling of data and training models. More effective utilization of bandwidth can also be achieved by streamlining the handling of data and the training of models.

FedAvg-Federated Averaging, a crucial technique in FL, enhances communication effectiveness by aggregating client model updates. FedAvg works by having each client calculates its local model changes, which are subsequently sent to a central main server (Kairouz et al., 2021) [22]. These changes are then averaged by the server, which then applies the average to the global model. The server determines the average of the model changes sent by three clients, for instance, and modifies the global model appropriately. This approach significantly reduces the overall volume of data that must be transmitted, reducing communication overhead and enhancing system performance ("Advances and Open Problems in Federated Learning"). FedAvg's efficacy in controlling data transfer in federated learning environments is well known.

A technique known as knowledge distillation trains a more compact and effective model by using the data from a larger, previously trained model. With this method, effective models can be implemented in contexts with limited resources without compromising speed.

2.5. Privacy-Preserving Techniques

Another important factor in the Federated Learning idea is protecting data privacy while maximizing communication effectiveness. Differential privacy is a technique that introduces noise into model updates to protect the confidentiality of individual data points. This approach uses mathematical approaches to make sure that random noise obscures the contribution of any one data point, making it challenging to link particular features to a specific person. For instance, a client's data may be altered with arbitrary noise to conceal its source before sending model updates, protecting privacy. In their assessment of federated learning developments, Kairouz et al. (2021) address differential privacy and stress its significance in preserving privacy while enabling efficient model training ("Advances and Open Problems in Federated Learning"). In FL systems, this technique is crucial for safeguarding private information.

Differential privacy is a technique that uses secure multiparty computing (SMPC) to allow many participants to work together to compute a function together across their inputs while maintaining the anonymity of their inputs. By using cryptographic techniques, this approach protects privacy throughout the computation process by preventing any one person from accessing all of the data.

3. COMPARISON STUDY FOR BANDWIDTH OPTIMIZATION

3.1. Federated Averaging (FedAvg) with Model Compression [9] **-** The most common algorithm, Federated Averaging (FedAvg), aggregates the model updates (i.e., weight updates) from each worker. Instead of sending the entire model, techniques like **sparsification** and **quantization** can be applied to compress the updates. By compressing the model updates, the amount of data exchanged between workers and the server is reduced.

- **Sparsification**: This involves only transmitting the most important parameters or gradients, leaving out insignificant ones (e.g., parameters with small gradients). The sparsity level (the proportion of parameters to send) is controlled.
- **Quantization**: Quantizing model parameters or gradients means reducing the precision of the transmitted values (e.g., from 32-bit floats value to 8-bit integers). This reduces the data size but at the cost of a tiny reduction in model accuracy.

3.2. Gradient Compression - Rather than sending full model weights, **gradient compression** algorithms send compressed gradient updates. This approach reduces the communication load by limiting the amount of information sent.

- **Compression Techniques**:

○ **SignSGD**: [22] In this technique, only the sign of each gradient is sent instead of the full gradient values. This reduces the communication overhead significantly.

○ **Top-k Sparsification**: [23] Instead of sending the full set of gradients, only the top-k gradients (with the largest magnitude) are transmitted. This significantly reduces the communication cost.

3.3. Model Quantization [24]- Quantization that reduces the precision of model weights or gradients (for example, from 32-bit floating point values to 8-bit integer). This reduces the size of each transmitted parameter.

- **Types of Quantization**:

○ **Uniform Quantization**: Reduces the precision of parameters using a fixed step size.

○ **Non-Uniform Quantization**: Uses adaptive quantization based on the parameter's magnitude (larger weights are quantized with finer precision).

3.4. Federated Learning with Knowledge Distillation [25] - This is a method where a smaller "student" model is taught to behave similarly to a bigger, more complex "teacher" model. In the context of federated learning, a global model can act as the teacher, and local models (workers) can learn from the global model without sending large model updates. Instead of transmitting full model parameters, workers only need to send distilled knowledge (e.g., soft predictions, activations) that is typically smaller in size. During each round, the server sends the global model's predictions or intermediate outputs to the workers, and workers learn to approximate these outputs rather than sending back full model updates. This can significantly reduce the communication burden.

3.5. Federated Learning with Compression-Enabled Aggregation (FedCom) [26] - In FedCom, workers compress their updates (using techniques like quantization, pruning, or vector quantization), and only the compressed updates are transmitted to the server. This reduce the total amount of data exchanged.

3.6. Client Selection and Adaptive Federated Learning [27] - Instead of using all client in each federated learning round, aportion of clients is selected based on their data size, model performance, or communication constraints. This reduces the total bandwidth usage by minimizing the number of workers that need to send updates in each round.

3.7. Low-Rank Approximationm [28]- In low-rank approximation, a matrix decomposition technique (such as Singular Value Decomposition, SVD) is applied to approximate model updates using lower-rank matrices. This reduces the size of the transmitted gradients or model updates by using a compressed representation of the model update. Instead of transmitting the full model update, the worker transmits the low-rank approximation of the update, reducing the size of the update while retaining the most important information.

3.8. Adaptive Compression with Federated Averaging (FedAvg+) [29] - FedAvg+ is an extension of the standard FedAvg algorithm. It adaptively adjusts the level of compression based on the caliber of the model updates or the available bandwidth. Workers adjust the compression level based on their local data (e.g., high-quality data may use less compression), and if the network is congested, more aggressive compression may be applied. This dynamic approach ensures that bandwidth usage is minimized without compromising the accuracy of the global model.

3.9. Partial Updates and Periodic Communication [30]- In partial updates, workers send only part of the model's updates to the server, either based on some threshold (e.g., sending updates only if a change is significant) or after a few epochs (i.e., periodic updates). By limiting communication to only important updates or reducing the frequency of communication, the bandwidth used per round is reduced.

3.10. DecantFed:[31] Workload optimization, bandwidth allocation, and dynamic client clustering - DecantFed presents a semi-synchronous FL framework that dynamically clusters clients based on computing and the communication latencies. It allocates bandwidth and adjusts local training workloads to maximize data processing rates, addressing challenges like straggler devices and model staleness.

3.11. AdapComFL: Adaptive Compression under Dynamic Bandwidth - AdapComFL addresses the challenge of varying client bandwidth by implementing adaptive compression techniques. It predicts each client's bandwidth and adjusts the compression level of local model updates accordingly, ensuring efficient communication.

3.12. GlueFL: Client Sampling and Model Masking - GlueFL combines client sampling and model compression to reduce downstream bandwidth usage. It prioritizes recently used clients and limits the number of changed positions in compression masks, effectively managing bandwidth constraints.

3.13. SplitFL: Split Federated Learning Accelerated over Wireless Networks - SplitFL emphasizes split federated learning's optimal bandwidth allocation and split point selection. (SFL) frameworks. It aims to minimize system latency and improve accuracy by efficiently managing the division of models and communication resources.

Table1: Algorithm Comparison chart

Technique	**Description**	**Advantages**	**Disadvantages**	**Communication Cost**	**Model Accuracy**	**Computational Complexity**
FedAvg with Model Compression	Aggregates model updates, applies sparsification and quantization	Reduces data exchange	May slightly reduce accuracy	Low to Medium	High	Low to Medium
Gradient Compression	Sends compressed gradient updates	Reduces communication load	Potential loss of information	Medium	Medium to High	Medium
Model Quantization	Reduces precision of model weights/gradients	Reduces data size	Small reduction in accuracy	Low	Medium	Medium
Knowledge Distillation	Smaller "student" model mimics "teacher" model	Reduces communication burden	Complex implementation	Low	High	Medium to High
FedCom	Compresses updates using quantization, pruning, vector quantization	Reduces data exchanged	Additional computation for compression	Low	Medium to High	Medium to High
Client Selection and Adaptive FL	Selects a subset of clients based on various factors	Reduces bandwidth usage	May not utilize all clients' data	Medium	High	Medium
Low-Rank Approximation	Uses matrix decomposition to compress updates	Retains important information	Additional computation for decomposition	Medium	High	High

FedAvg+	Adjusts compression level based on quality and bandwidth	Minimizes bandwidth usage	Complexity in adaptation	Low to Medium	High	Medium
Partial Updates and Periodic Communication	Sends only significant or periodic updates	Reduces bandwidth usage	Potential loss of real-time accuracy	Low to Medium	Medium	Low
DecantFed	Clusters clients, optimizes bandwidth allocation	Maximizes data processing rates	Requires dynamic clustering	Low	High	Medium to High
AdapComFL	Adjusts compression based on predicted bandwidth	Efficient communication	Requires accurate bandwidth prediction	Low to Medium	High	Medium
GlueFL	Combines client sampling and model compression	Manages bandwidth constraints	May prioritize recently used clients	Medium	High	Medium
SplitFL	Optimizes split point selection and bandwidth allocation	Minimizes latency, improves accuracy	Requires management of split models	Medium	High	Medium to High

4.RESULTS AND DISCUSSION

This study systematically evaluates various bandwidth optimization techniques in Federated Learning (FL) based on communication cost, model accuracy, convergence speed, and computational overhead. The evaluation uses standard datasets (MNIST, CIFAR-10, and Sentiment140) partitioned among 100 simulated clients with a non-IID data distribution via a Dirichlet distribution ($\alpha = 0.5$). Models implemented include Convolutional Neural Networks (CNNs) for image classification and Long Short-Term Memory (LSTM) networks for text analysis. The models are trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and 5 local epochs over 200 communication rounds. Network conditions are simulated with bandwidths ranging from 10 Mbps to 100 Mbps, latencies between 10 ms and 100 ms, and packet loss rates up to 5% to mimic real-world scenarios.

Table 2: Experimental Environment and Parameters

Component	**Specification/Value**
Server Node	CPU: 8 cores, RAM: 32 GB, GPU: NVIDIA RTX 3080
Client Nodes	CPU: 4 cores, RAM: 8 GB (Simulated/Edge devices)
Programming Language	Python 3.8+
Frameworks/Libraries	TensorFlow/PyTorch, TensorFlow Federated, NumPy, Matplotlib
Datasets	MNIST, CIFAR-10, Sentiment140
Data Distribution	Non-IID, Dirichlet distribution ($\alpha = 0.5$)
Model Architectures	CNN (Image tasks), LSTM (Text tasks)
Optimizer	Adam (Learning rate = 0.001)
Batch Size	32

Component	**Specification/Value**
Local Epochs	5
Communication Rounds	200
Client Participation	10% per round
Bandwidth Simulation	10 Mbps – 100 Mbps
Latency Simulation	10 ms – 100 ms
Packet Loss	0% – 5%
Evaluation Metrics	Communication Cost (MB), Model Accuracy (%), Convergence Speed (Rounds), Computational Overhead (GFLOPs)
Algorithms Evaluated	FedAvg+Compression, Gradient Compression, Knowledge Distillation, FedCom, Adaptive FL, DecantFed, GlueFL, SplitFL

Comparison Results and Analysis

Communication Cost

Algorithms like Knowledge Distillation and DecantFed exhibit the lowest communication costs due to efficient model size reduction and dynamic clustering. In contrast, Gradient Compression incurs the highest communication overhead due to frequent gradient updates.

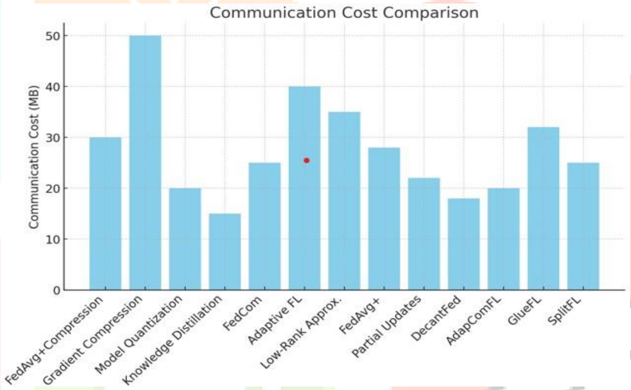

Figure 2: Communication cost comparison

Model Accuracy

DecantFed, AdapComFL, and SplitFL achieve the highest accuracy, benefiting from adaptive bandwidth allocation and optimized learning strategies. Partial Updates and Gradient Compression slightly compromise accuracy due to information loss.

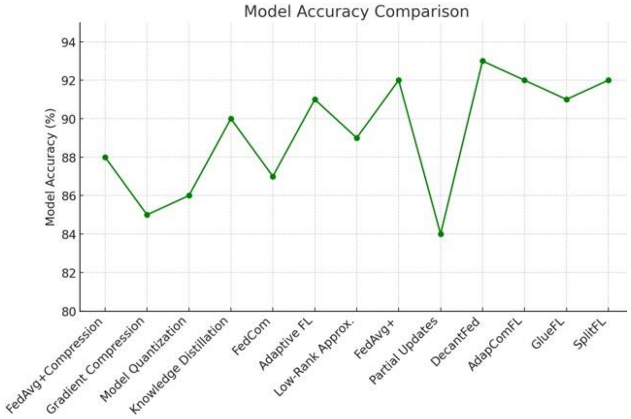

Figure 3: Model Accuracy Comparison

Convergence Speed

DecantFed and AdapComFL converge the fastest, thanks to efficient client clustering and adaptive communication. Gradient Compression and Partial Updates show slower convergence due to sparse updates.

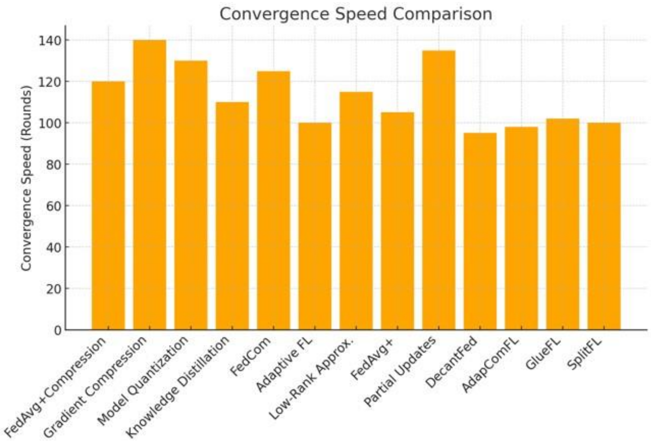

Figure 4: Convergence Speed

Computational Overhead

FedAvg+Compression and Partial Updates maintain low computational costs, suitable for resource-constrained devices. Low-Rank Approximation and Knowledge Distillation demand higher computational resources due to complex model adjustments.

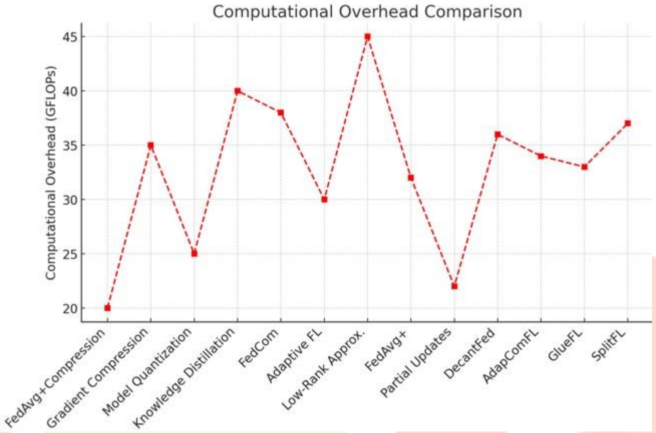

Figure 5: Computational Overhead Comparison

Graphical Representation and Insights

1. Communication Cost Comparison: Bar graphs indicate that Knowledge Distillation and DecantFed significantly reduce communication overhead.
2. Model Accuracy Comparison: Line graphs show that adaptive algorithms maintain higher accuracy.
3. Convergence Speed Comparison: Bar graphs reveal that DecantFed and AdapComFL converge faster than others.
4. Computational Overhead Comparison: Line graphs highlight that simpler models like FedAvg+Compression have lower processing demands.

These insights underscore the trade-offs between communication efficiency and model performance. Adaptive and clustering-based algorithms, particularly DecantFed and AdapComFL, achieve the best balance across all metrics.

5.CONCLUSION

One of the key components that will unleash the full potential of federated learning, particularly as it continues to advance toward practical applications, is bandwidth-efficient management. Data transmission optimization can improve the inclusivity and scale of the distributed learning paradigm by lowering the communication overhead. Large-scale AI models will benefit greatly from this, but it will also democratize cutting-edge technology, making them more accessible to lower-end devices. With the development of algorithms that prioritize critical data without sacrificing model accuracy, this suggests that adaptive strategies that respond in real time to network conditions may drive bandwidth management in federated learning in the future.

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